# Waiting for the R Train: Public Transportation and Employment

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#### Abstract

Expanding employment opportunities for citizens has become an increasingly central goal of public policy in the United States. Prior work has considered that the inability of households to spatially access jobs may be a driver of unemployment. The provision of public transportation provides a viable policy lever to increase the number of job opportunities available to households. Previous research has yielded mixed results regarding whether household location is an important factor in determining employment status. Several papers have identified mobility as a limiting factor for obtaining a job, particularly in regards to private vehicle ownership. The location of economically developed neighborhoods and the citing of public transportation are conceivably codetermined, presenting an endogenous relationship. It is therefore unclear if public transportation access is actually contributing to neighborhood job market outcomes. This paper will use the incidence of Hurricane Sandy striking New York City on October 29, 2012 and the resulting exogenous reduction in public transit access to particular neighborhoods as a natural experiment to test for the effect of public transportation on employment outcomes. This study identifies a significant causal effect linking public transportation access to neighborhood unemployment rates, particularly amongst subgroups dependent on public transit.

Key Words: Spatial Mismatch, Employment, Public Transportation, Access, Mobility

## 1. Introduction

There has been substantial interest in public policy circles in recent years regarding strategies of "job creation" and fostering "job access." These terms are rarely provided with concrete definitions and are instead meant to capture an alleged capacity on the part of government to decrease unemployment, or increase the quality of jobs that are available to individuals. Making job opportunities more spatially accessible represents a plausible policy lever to improve employment outcomes amongst urban residents. If government improves transportation networks, the number of jobs available to a typical individual will be increased, potentially improving the speed with which workers match to firms and improving the quality of matches.

Job access is closely related to issues of urban sprawl and the theory of spatial mismatch, both of which consider spatial gaps between workers and jobs. For populations reliant on public transportation, the ability to access employment is closely tied to the usability and extent of the region's public transportation network. There is empirical evidence that populations with better access to jobs through public transportation networks also enjoy lower rates of unemployment (Holzer et al., 2003; Kain, 1992; Sanchez et al., 2004). Contrastingly, studies have argued that private vehicle ownership is the dominant transportation variable driving differences in employment outcomes (Baum, 2009; Ong and Miller, 2005; Raphael and Stoll, 2001; Taylor and Ong, 1995).

Locations that occupy geographically central locations, or have exogenously developed as centers of economic activity or affluence, will be more likely to see local public transit investment due to the higher economic returns to transit infrastructure in such areas. The effect of Hurricane Sandy on New York City's public transportation

infrastructure presents an unprecedented natural experiment to investigate a causal relationship. Using the truly exogenous reduction in public transportation that occurred in particular neighborhoods, this study will provide evidence for a causal relationship between public transportation access and local unemployment.

### 2. Related Research

This section forms a basis for the current study in the foundational contribution of Kain (1968). Subsequently, this section will describe more recent and closely related works, particularly those that look specifically at transportation and the accessibility of jobs within US metropolitan areas.

Post-war North American cities have undergone suburbanization of employment, accompanied by a decrease in the relative importance of the manufacturing economy (Wilson, 1996). This shift in the labor market arose concurrently with rising inner-city unemployment. Kain (1968) represents the first effort in the literature to draw an empirical connection between location of housing and the propensity to be unemployed. Kain (1968) specifically attempted to explain the unusually high rates of unemployment that persisted in black neighbourhoods in the inner cities of Chicago and Detroit. While previous investigations had exclusively blamed job market discrimination for the gap in employment between white and black neighbourhoods, Kain (1968) suggested that the locational characteristics of neighbourhoods with respect to job centers might also play a strong role in determining job market outcomes.

Since Kain (1968), several papers have reviewed or extended the spatial mismatch hypothesis (Brueckner and Zenou, 2003; Coulson et al., 2001; Gobillon et al., 2007;

Raphael, 1998; Rogers, 1997; Smith and Zenou, 2003; Taylor and Ong, 1995). To this point there have been conflicting findings regarding whether spatial mismatch is a primary driver of high unemployment amongst inner-city populations.

Harrison (1972) looked at large US metros and found no conclusive evidence that spatial isolation was causing unemployment amongst black populations. The study ceded the difficulty of identifying a causal relationship, calling for a longitudinal study to track the movement of households through time. Farley (1982) presented empirical evidence that spatial dimensions of employment markets cause higher rates of unemployment amongst black populations, particularly in northern US metros. The study used controlled regressions and estimated that 15% of the gap in white-black unemployment could be derived as a consequence of housing segregation and suburban employment location. Immergluck (1998) applied an investigation of spatial mismatch to Chicago, finding a strong correlation between localized job market opportunities and the likelihood of being employed.

The importance of spatial dimensions of labor markets can be generalized beyond inner-city minority populations to investigations into the importance of job accessibility to workers generally. It is important to recognize that isolation from opportunities is a consequence of inaccessibility, rather than distance. If workers have efficient transportation that connects them to jobs then distance can plausibly be overcome. This reasoning has led to the growth of so-called 'transportation mismatch' literature, which purports to show that if isolated populations are extended transportation opportunities, unemployment gaps may be abated.

Numerous prior papers have demonstrated that increasing rates of private vehicle

ownership amongst low-income or minority populations may be an effective means of reducing unemployment amongst these populations (Baum, 2009; Gordon and Kumar, 1989; Kawabata, 2003; Ong and Miller, 2005; Raphael and Stoll, 2001; Taylor and Ong, 1995). Taylor and Ong (1995) found that commute times amongst minority workers were actually shorter than for white workers, in apparent contradiction to the spatial mismatch hypothesis. Driving to work alone –as apposed to alternative modes– was shown to be a significant predictor of a short commute time across race groups and neighborhoods. Raphael and Stoll (2001) examined the gap in employment outcomes between minority and white workers, finding that lower rates of car ownership amongst minority populations explained 45% of the black-white employment gap, and 17% of the Hispanic-white employment gap. Ong and Miller (2005) argued that there is surprisingly scant evidence supporting spatial mismatch being a major driver of differential unemployment rates for black workers, and presented compelling empirical evidence that the lack of a private vehicle significantly limits job prospects of black workers in the context of Los Angeles.

Despite evidence of a beneficial marginal effect of car ownership, it is not clear that aggregate regional accessibility is well served by increasing private vehicle use. In dense urban environments in the US, road networks are typically filled past their designed capacity during peak hours, resulting in congestion. Although providing a car to a marginal household may increase the job prospects of that household, increased car ownership also inflicts a cost on existing commuters through higher congestion. The effect of increased car ownership on aggregate mobility and accessibility is therefore ambiguous, with the negative effects being more pronounced in high congestion cities.

The provision of public transit provides a plausible means to increase employment access while not contributing to road congestion. Thomas Sanchez furnishes the literature with US case studies looking directly at public transit characteristics – such as the nearness to a bus or subway stop, or transit service frequency – relating high transportation access to lower levels of unemployment. Sanchez (1999) analyzed access to public transportation for poor black communities in Portland, Oregon and Atlanta, Georgia, finding that unemployment is higher for those residents who live more than 400 meters from a public transit node. Sanchez et al. (2004) looked at a wider sample of cities and found transit access to be negatively related to the likelihood of a household being on government assistance. Despite these seemingly strong findings, Sanchez et al. (2004) admits to possible identification issues, pointing out that the locational choices of households "result from complex and intricate factors" that may be codetermined with economic success.

Bollinger and Ihlanfeldt (1997, 2003) estimated local employment growth attributable to the construction of rail infrastructure in the Atlanta region. The authors found that neighborhoods adjacent to a new rail station had no significant increase in local employment. Bollinger and Ihlanfeldt (1997) suggest this is attributable to the low ridership experienced by the rail system in the highly auto-oriented environment of Atlanta.

Kain (1992) provided an exhaustive review of prior spatial mismatch research at the time. Kain (1992) contains a direct discussion of the merits of promoting mobility as a means to overcome the problems of spatial mismatch, particularly directing the discussion at Hughes and Madden (1991). Hughes and Madden (1991) advocated

integrative housing policies that would end spatial isolation amongst black populations, suggesting that transportation based policies are untenable because they accept persistent segregation. Kain (1992) responded that increasing suburban access to inner-city residents is actually pro-integrative as it reduces the daily experience of isolation. Gobillon et al. (2007) investigated transportation-based solutions to spatial mismatch and found evidence for the efficacy of such policies to be mixed.

Identifying the causal effect of transportation investment on employment must overcome the potentially endogenous processes by which transit provision and local economic growth are determined. Specifically, it is unclear if transportation infrastructure causes changes in local labor market outcomes or rather the citing of transportation is determined by preexisting local economic conditions. A related argument put forward by Knight and Trygg (1977) is that the impact of rail infrastructure on accessibility is limited because urban rail is almost exclusively cited in areas that can be easily accessed by car to begin with. Ihlanfeldt and Sjoquist (1998) provide a discussion of the potential endogeneity that occurs when using household location as a predictor of employment outcomes: "The problem with this approach is that while job access may affect employment, employment may also affect the magnitude of the measure of job access." Ihlanfeldt and Sjoquist (1998) considered past evidence to be inconclusive regarding the presence of a causal role of transportation access on employment. A primary focus of this paper will be to establish that the accessibility provided by public transportation has a causal relationship with neighborhood unemployment, particularly amongst those without access to a private vehicle.

Exclusively studying youth populations has provided a partial solution to the

identification problem because the location of a youth's home is more plausibly exogenous. If it is assumed that youth have no influence over household locational choice then a youth's location may be orthogonal to their employability; however, job market ability has been shown to be highly stable across familial generations (Clark, 2014), suggesting that the neighbourhood choice of parents may be spatially stratifying youth populations by ability. Ellwood (1986) examined youth employment outcomes in Chicago, finding that although isolated black populations commuted significantly farther on average than whites, spatial isolation had only a small effect on their ability to actually secure employment. Ihlanfeldt and Sjoquist (1990) delivered compelling evidence that "nearness to jobs" through the transportation network is strongly correlated with unemployment amongst youth populations in Philadelphia. O'Regan and Quigley provided a series of papers on the connection between neighbourhood accessibility and youth employment rates (O'Regan and Quigley, 1996, 1998), generally finding that more centrally located neighbourhoods provide superior job market outcomes for youth.

Holzer et al. (2003) supplies a study that is closely related to the current paper in its attempt to overcome the identification problem through use of a natural experiment. Holzer et al. (2003) recognized, "No study has identified a clear exogenous source of variation in spatial access to employment opportunities." Holzer et al. (2003) used the 1997 expansion of the San Francisco region's Bay Area Rapid Transit (BART) system, which extended service to a particular suburb, as an exogenous shock to the labor pool available to firms located along the new BART route. Holzer et al. (2003) found that firms along the extension hired more Hispanic residents from the inner city after the extension was completed, although found no significant impact on black employment.

The exogeneity assumption made by Holzer et al. (2003) is suspect because it ignores that the citing of transit infrastructure may be codetermined with economic activity (see Knight and Trygg, 1977). The citing of the new BART line was not random, but was specifically located along a route where planners foresaw a future demand for commuting. Furthermore, exogeneity of the event assumes that the extension played no factor in firm locational choice in the years leading up to the actual opening of the new rail route. It is likely that firms that chose to locate along the new line were predisposed to taking advantage of the inner-city labor pool, as accessible labor is a natural consideration in firm locational choice. Therefore, the finding that firms along the rail extension hired a higher percentage of Hispanic workers cannot be simply attributed to increased mobility of these residents. A central contribution of the present paper will be to utilize an unplanned, and unforeseen variation in infrastructure to avoid these barriers to causal inference.

Several of the aforementioned papers share the same barrier to identification: disentangling the endogenous relationship between localized economic development and the citing of public transit. In order to infer a causal impact of public transportation on neighborhood employment, the effect of employment on transportation infrastructure construction must be removed. The remainder of this paper will explicitly address this confounding relationship.

### 3. Data

This paper relies on American Community Survey (ACS) data, collected by the US Census Bureau. In order to identify trends through time, one-year estimates are used

for years 2010 through 2013. The ACS Public Use Microdata Sample (PUMS) provides annual individual level observations, including employment status, for a randomly selected 1% of the US population. Variables are taken directly from the Integrated Public Use Microdata Series (IPUMS) data products (Ruggles et al., 2014).

All individuals living outside of New York City are dropped from the sample. Only individuals at least 16 years of age and in the labor force are retained for analysis. Of individuals at least 16 years of age and living in New York City, 60.6% are in the labor force. This creates a sample of 136,726 individual level observations, split roughly evenly across the four years observed.

The smallest identifiable geographic unit is the Public Use Microdata Area (PUMA). Each PUMA contains at least 100,000 persons. PUMA boundaries are contiguous with New York City boundaries, covering the entire city.

Income is represented by the individual respondent's total pre-tax personal income, normalized to 2013 dollars. Income is represented in regressions in logged form.

Dummy variables for race are generated for each observation. White, black and Asian are considered mutually exclusive race groups; however, Hispanic ethnicity is derived from a separate survey question and therefore an individual can be considered as both Hispanic and either white, black or Asian.

Regressions also use Federal Emergency Management Agency (FEMA) insurance payout data, which cover payouts to housing owners and renters under the Individuals and Households Program (IHP). Observations can be identified as resulting from damage caused by Hurricane Sandy. All payments resulting from other events are dropped. IHP data is used as a proxy for the intensity of local storm damage. FEMA reports these data

at the Zip Code Tabulation Area. Data has been cross-walked to PUMAs using the Missouri Census Data Center's Geographic Correspondence Engine, providing an estimate for the average individual's FEMA payout by PUMA.

Summary statistics for the entire sample of New York City workers are provided in Table 1.

### 4. Hurricane Sandy and the R Train

Hurricane Sandy made landfall in New York City on October 29th, 2012. Amongst instances of infrastructure damage across the region, the storm resulted in the flooding of the Montague Street Tunnel, which lies beneath the East River and connects Brooklyn to Manhattan (shown in Figure 1). The Montague Street Tunnel is primarily used by the R Train subway, which represents the major public transit connection linking neighborhoods on the western edge of Brooklyn to Manhattan. After the hurricane, R Train service was immediately interrupted due to the flooding of the Montague Street Tunnel. Over the subsequent two months the tunnel was drained and repaired, reopening for R Train service on December 21st, 2012. In the months after the tunnel reopened it was determined by the Metropolitan Transportation Authority (MTA), who operates the tunnel, that additional repairs would be required. It was announced to the public on June 5th, 2013 that a long-term closure would be necessary. The tunnel was subsequently closed for repairs between August 2nd, 2013 and September 14th, 2014. During closure the R Train was split into two routes, divided by the East River.

# Figure 1. Neighborhoods Impacted by R Train Closure





The closure of the R Train created significant commuting delays for workers who lived along the R Train route in Brooklyn and worked in Manhattan, potentially putting strain on their ability to maintain employment. Additionally, unemployed individuals living along the Brooklyn R Train route may have altered their job search strategy in response to the altered transit service. Manhattan job centers that were previously within commuting distance ceased to be viable options for employment because they could not be reached in a reasonable commuting time. This point is central to the identification strategy: the removal of R train service for Brooklyn represents an exogenous shock to job access for particular residents. If it is true that public transportation access has a causal impact on job market outcomes, then a sudden and unexpected reduction in public transportation service should result in reduced job market success for the residents of impacted neighborhoods.

The context of New York City is unique within the US in regards to high rates of public transportation use and low rates of private vehicle ownership. In 2012, 57% of the New York City workforce reported using public transportation as their primary mode of commuting to work and only 44% of households reported owning a private vehicle. Amongst the 387 other principal cities of defined metropolitan areas in the US in 2012, the average rate of public transit use for commuting was only 4.3%, while the average rate of household vehicle ownership was 89%. Findings for New York City therefore reflect the specific realities of a dense urban environment with significant public transit use.

#### 5. Methodology

This study uses a difference-in-difference approach to identify the impact the R Train closure had on employment outcomes for affected neighborhoods. A difference-indifference approach allows for the estimation of how employment outcomes changed in the affected neighborhoods, while controlling for regional employment trends through time, as well as fixed characteristics that may differentiate the affected and unaffected neighborhoods. To further reduce bias in estimation, borough fixed effects are used in all

regressions, to control for localized employment conditions.

Of the four years of observations used in analysis, only 2013 is considered as having been 'treated' by the closure of the R Train. The R Train was closed for a fivemonth period in 2013, whereas it was closed for less than two months in 2012. The effect of the extended 2013 closure on employment should have the greatest magnitude and so is the topic of empirical investigation. Estimation will rely on representing the 2013 closure as a negative shock to employment prospects. The brief 2012 closure does not pose a barrier to establishing a causal effect, as any negative employment effects on treatment neighborhoods in 2012 will result in an underestimation of the true 2013 effect.

Three PUMAs are identified that are primarily reliant on the R Train in order to reach job centers in Manhattan and beyond: Community Districts 6, 7, and 10 (see Figure 1), all of which are in western Brooklyn. Although PUMAs represent a coarse geographic unit, this study is fortunate that these three PUMAs align very closely to the neighborhoods one would hypothesize to be heavily reliant on the R Train. The boundaries of treatment PUMAs are consistent through time.

Community Districts 6, 7, and 10 represent a highly diverse population. The median income of New York City in 2013 was \$35,000. The median income of Community District 6 was substantially higher at \$65,000, Community District 7 was substantially lower at \$25,000, and Community District 10 was somewhat higher than the city median at \$42,000. These three community districts had a greater share of white residents (67%) and a lower share of black residents (4%) than the citywide shares, which were 50% and 24% respectively.

In testing the impacts the tunnel closure had on these neighborhoods it is useful to

confirm that these areas were not disproportionately affected by the direct impacts of Hurricane Sandy; otherwise, the observed negative employment effects may be simply attributable to general damage from the storm. FEMA provides data on insurance payouts under the IHP, providing a reasonable proxy for comparing hurricane damage between PUMAs. The average individual in New York City received \$69 in hurricane recovery assistance under IHP, while the average individual in the treatment neighborhoods received only \$15. It appears that if anything, the treatment neighborhoods received less damage than was typical. An exception to this average is the coastal neighborhood of Red Hook in Community District 6, which suffered significant damage to building stock as a result of the hurricane. Red Hook residents only comprise 2.7% of the total population of treated PUMAs; furthermore, results are robust if Community District 6 is considered as a control rather than a treatment neighborhood. To guard against the potential direct impacts of storm damage on local economic conditions, the average FEMA payout within the individual's PUMA is controlled for in regressions.

As discussed in the previous section, 2013 brought a substantial reduction in transit service for the treated neighborhoods. Observations that are both located within a treatment neighborhood and were recorded in 2013 are referred to as the treatment group. Defined in this way, there are 2,082 treatment observations, within a sample of 136,726.

The methodology presented here overcomes potential codetermination between economic conditions and transportation infrastructure by exploiting random variation in infrastructure. There is no possibility that Hurricane Sandy's impact on the Montague Street Tunnel was planned or predicted, meaning initial local economic conditions were orthogonal to this variation.

# 6. Results

The impact of the R Train disruption on the treatment neighborhoods can be glimpsed in Figure 2. Between 2010 and 2012 the rate of unemployment decreased significantly within the treatment neighborhoods, falling from 9.8% to 8.0%. Unemployment in the remainder of New York City was relatively stable over this period, falling slightly from 11.4% to 11.1%. This trend was starkly reversed in 2013 wherein the neighborhoods along the Brooklyn R Train saw a rise in unemployment (8.0% to 8.4%) while in other neighborhoods unemployment fell substantially (11.1% to 9.7%). This departure in outcomes in 2013 is suggestive that job market conditions changed in the treatment neighborhoods in 2013, making employment more difficult to secure or maintain.



Figure 2. Unemployment Trends in Treated and Control Neighborhoods

The impact of the R Train disruption on commuters would only be felt within the treated Brooklyn neighborhoods if there were a substantial proportion of the local workforce using the R Train to reach employment, the most probable destination being job centers in Manhattan. IPUMS provides workplace location data at the borough level within New York City. Of those living within the treatment neighborhoods in 2012, 43% of the workforce commuted to Manhattan for employment. Within the treatment subpopulation that commuted to Manhattan, 84% reported using the subway to commute. This suggests the R Train represented an important link to employment for the treatment neighborhoods. The Hispanic population departs somewhat from these statistics, with only 32% of the Hispanic workforce commute to Manhattan. Workers earning high incomes were more likely to commute to Manhattan. Workers earning above the median income worked in Manhattan at a rate of 53%, compared to 33% for workers earning below the median. For workers earning in the bottom 10<sup>th</sup> percentile of incomes, the probability of working in Manhattan was similarly 33%.

In accordance with Angrist (2001) and Angrist and Pischke (2009) OLS is used throughout this study rather than an estimation method specific to limited-dependent variables.<sup>1</sup> Table 2 provides a regression for the full sample of New York City workers. As economic conditions improved following the financial crisis of 2008, the probability

<sup>&</sup>lt;sup>1</sup> Angrist (2001) and Angrist and Pischke (2009) argue for dispensing with limited dependent variable models in favor of conventional OLS approaches in cases where the research interest is the estimation of a particular causal effect. The ostensible advantage of limited dependent variable methods is tied to reconciling structural parameters rather than isolating causal effects. The statistical significance of the estimated partial effect of interest in the current study holds in the case of estimation using a logit or probit model; however, the partial effect provided by OLS is more readily interpretable.

of unemployment amongst New York City workers fell. Year fixed effects show the probability of being unemployed decreased across the four years studied. Column 2 adds individual level controls for age, age squared, logged annual income, and whether the individual had access to a private vehicle. Subsequent regressions include a full set of controls for education level. Kasarda (1989) provides evidence from US inner cities demonstrating that a great deal of variation in employment outcomes amongst spatially isolated households can be explained by education level. Column 4 in Table 2 adds controls for race group. Finally, column 5 controls for the PUMA level variation in local storm damage. The interpretation of control coefficients is not of particular interest because many of the controls are codetermined. The central result, indicating the impact of living in the treatment neighborhoods in 2013, is robust to the inclusion of these controls.

After controls are in place, the estimated effect on an individual attributable to living adjacent to the R Train in 2013 is an increase in the probability of being unemployed of 1.4 percentage points (Table 2, column 5). The result is highly statistically significant, as well as representing a large effect in practical terms. This finding is completely consistent with a transportation mismatch hypothesis, in which a lack of mobility results in inferior employment outcomes. This observed effect cannot be explained by the codetermination of transit location and economic activity, demonstrating a causal connection between transit provision and neighborhood employment outcomes.

Estimated neighborhood level effects can be attributed to a reduction in neighborhood connectivity. However, neighborhood self-selection may still exist, which presents a barrier to inferring a causal effect on individual workers. If households are able

to participate in neighborhood sorting in response to the R Train closure between the time when the hurricane damaged the Montague Street Tunnel (October 29th, 2012), and the end of 2013 (marking the last day in which 2013 ACS data may have been collected) then particular households could be self-selecting into neighborhoods based on the R Train closure.

The ACS contains a variable displaying how long ago an individual moved into their current residence. One possibility that would suggest neighborhood sorting is that unemployed individuals moved to the treatment neighborhoods preferentially. This can be empirically investigated. The controlled difference-in-difference regression was repeated, partitioning the sample into those who moved within the past year (recent movers), and those who did not. As would be predicted by a neighborhood sorting argument, the 'impact' of the R Train closure is far greater for those who recently arrived in the treatment neighborhoods, suggesting that the unemployed are preferentially moving to affected neighborhoods. The effect of living in a treatment neighborhood amongst recent movers is an increase in the unemployment rate of 3.2 percentage points. The effect on longer-term residents is only 1.1 percentage points. Recent movers claim a 13.7% population share within the treatment neighborhoods in 2013. The effect of the R Train closure on non-recent removers is still highly statistically significant.

A second potential source of individual level bias is the possibility that employed residents disproportionately left the treatment neighborhoods or dropped out of the workforce in response to the R Train closure. Any large exodus from the neighborhood could be observed as a drop in average home value or rent in 2013. Table 3, columns 1 and 2 provide difference-in-difference estimates for average home value and rent paid.

There is no significant effect on either of these variables from being in a treated neighborhood, although the point estimates demonstrate a negative effect.

Workers who left the treatment neighborhoods in 2013 cannot be observed and therefore their employment characteristics cannot be directly examined. Changes in neighborhood demographics can be observed and used to check for shifts in neighborhood composition. Table 3, columns 3-8 present the partial effect of being in the treatment group on the likelihood or magnitude of relevant demographic characteristics. There is an observable shift in workforce demographic characteristics in treatment neighborhoods including an increase in the proportion of black and Hispanic residents, an increase in age, and a decrease in the probability of holding a graduate degree. Although these observations provide some evidence of a shift in neighborhood demographics tied to the R Train closure, they do not pose a direct problem for estimation as they are all explicitly entered into the difference-in-difference model as controls. Therefore, changes in socioeconomic make-up of the neighborhood cannot be cited as an explanation of the increase in unemployment found in this study. However, the potential for shifts in latent ability characteristics that are not controlled for prevents the translation of clear neighborhood level effects to individual level impacts.

The following section will exploit variation in a worker's dependence on public transportation to look for evidence that the observed rise in unemployment can be linked to reductions in mobility.

## 7. Results: Effect of Private Vehicle Access

Several prior studies have found a relationship between vehicle ownership and an

increased propensity to secure employment (Baum, 2009; Gordon and Kumar, 1989; Kawabata, 2003; Ong and Miller, 2005; Raphael and Stoll, 2001; Taylor and Ong, 1995). If the employment effect found in the current study is in fact a result of the loss of R Train service, this impact should be larger amongst those who are most dependent on public transit. The ACS asks respondents how many vehicles are kept at the household, and are available to the household member. In this section the sample is split in two: those with no vehicles available at all, and those with at least one. 57.7% of the workforce has access to at least one vehicle.

Table 4 (columns 1 and 2) conforms to expectations regarding the role of vehicle ownership. Education and income are controlled in all regressions so the impact of car ownership can be interpreted as independent of an income effect. Individuals with access to a vehicle were found to experience a significant increase in unemployment of 0.7 percentage points as a result of the transit disruption, while individuals without access to a vehicle were found to suffer a much larger increase of 2.2 percentage points. The effect of reduced transit is clearly more pronounced amongst those who lack an outside option for transportation.

This section's findings strengthen that of the previous section by drawing a clear line in the data between job access through the public transit system and employment outcomes.

#### 8. Results: Differences Across Race Groups

Exploring differences in US employment outcomes between race groups has received significant attention in the literature; furthermore, investigations into the spatial mismatch hypothesis are often predicated on the observed spatial isolation of urban black populations. It is therefore of interest whether the impact of spatial isolation is particularly acute amongst minority populations.

This section divides observations into groups of race and ethnicity. Table 4 (columns 3-6) shows how the impact of job access is highly variable across race groups. For the entire population (Table 2, column 5), the impact of the R Train closure was estimated to be an increase in unemployment in affected neighborhoods of 1.4 percentage points. Amongst white residents, the estimated effect is significantly less (0.7 percentage points), falling short of statistical significance. For Asian residents, the effect is not significantly different from the aggregated estimate, and is estimated as a highly significant increase in unemployment of 1.3 percentage points. For black residents the estimated effect is 1.7 percentage points, also statistically indistinguishable from the aggregate estimate. In agreement with Holzer et al. (2003) and Andersson et al. (2014), this study finds the unemployment rate within the Hispanic population to be most affected by job accessibility. The closure of the R Train is associated with a 3.4 percentage point increase in the unemployment rate of Hispanic residents. In practical terms, the increase in unemployment attributable to the R Train closure represents a precipitous drop in the employment prospects of Hispanic residents in the treated neighborhoods.

Spatial mismatch has often dealt exclusively with the lagging employment outcomes of isolated black populations. The current study finds that, although black residents of the treatment neighborhoods experienced higher rates of unemployment in each of the four years studied relative to Hispanic residents, the impact of transit access

on employment is much larger amongst Hispanics. Holzer et al. (2003) put forward a number of possible explanations for a pronounced effect amongst Hispanics. Firstly, if a particular subgroup is more dependent on employee referrals to secure employment, the loss of jobs within the community may have a multiplier effect in which a lost job lowers the prospects of securing employment for those within the unemployed individual's social network. Prior research has found that referrals play a disproportionately powerful role in securing employment amongst Hispanics and new immigrants (Elliott, 2001; O'Regan, 1993). Holzer et al. (2003) also suggests Hispanics may be more willing to travel a greater distance to secure employment; however, this seems a less plausible explanation for the results found here, as the treated Hispanics are observed to be less likely to travel outside of Brooklyn for employment than other groups.

An alternate explanation for the pronounced effect among Hispanics is the high rate of subway use in New York City amongst Hispanic commuters: 43.9%, compared to 40.0% amongst blacks and 39.2% for whites. These findings are consistent with national investigations that show high public transit use amongst foreign-born populations (McKenzie and Rapino, 2011).

In the current study, spatial isolation from jobs appears to exert a larger influence on black communities than white communities. However, the impact within the Hispanic population is significantly greater than within either white or black populations, suggesting that future investigations into spatial mismatch should pay greater attention to the apparently large impacts of job accessibility amongst Hispanics.

#### 9. Conclusion

The advent of Hurricane Sandy flooding the Montague Street Tunnel represents a unique natural experiment for investigating the impact of job accessibility through public transportation on employment outcomes. There is compelling evidence that a sudden decrease in public transportation triggered a significant hardship for the job market prospects of affected workers. This finding provides an argument against eliminating existing urban transit services, as reductions in service may have significant and costly effects realized through increased local joblessness. An inability for agencies to fund current transit levels and to contemplate service reductions is not an uncommon scenario (Gomez-Ibanez, 1996; Nelson et al., 2007).

Household locational choice is not exclusively determined by current employment or employment prospects. Locational choice is instead the result of a complex decision function of which one element is employment. It is therefore not sensible to invoke an overriding theory of spatial equilibrium with respect to jobs. Workers may be compelled by finances, family ties or community networks to remain in a neighborhood even if it does not perfectly suit their needs for employment or mobility. This reality opens policy space for efficiency gains through maintaining transit to neighborhoods with otherwise poor job accessibility. Establishing a deeper understanding of the extent and speed with which households relocate in response to transit alterations would be a fertile area for future research.

This study finds strong evidence that public transportation access plays a meaningful role in setting the level of local unemployment. During contemplation of public transportation policy the localized employment effects are rarely explicitly considered; however, the impact appears to be large. In New York City the effect is

particularly pronounced within the Hispanic population, and amongst those without access to a private vehicle. Maintaining public transit service to job centers should be prioritized in transportation and labor policy, specifically within congested metropolitan areas where increasing private vehicle ownership may be inefficient due to negative externalities.

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# Tables

Variable	Mean	Std. Dev		
Unemployed	0.108	0.31		
Adjacent to Brooklyn R Train in 2013	0.015	0.122		
Adjacent to Brooklyn R Train	0.06	0.237		
Year: 2010	0.243	0.429		
Year: 2011	0.248	0.432		
Year: 2012	0.253	0.435		
Year: 2013	0.256	0.436		
Age	41.433	13.821		
Log of Annual Income	9.964	2.297		
Access to a Vehicle	0.577	0.494		
High School Graduate or GED	0.864	0.343		
Some College Completed	0.648	0.478		
College Graduate	0.405	0.491		
Master's or Professional Degree	0.163	0.37		
PhD	0.016	0.125		
White	0.496	0.5		
Black	0.25	0.433		
Hispanic	0.23	0.421		
Asian	0.156	0.363		
Storm Damage per Person (\$100s)	0.694	1.903		
Obs.	136726			

**Table 1: Summary Statistics** 

(1)(2)(3)(4)(5)Adjacent to Brooklyn R Train $0.13^{**}$ $0.15^{**}$ $0.05^{**}$ $0.002$ $(0.002)$ $(0.002)$ Adjacent to Brooklyn R Train $028^{**}$ $-0.006^{**}$ $0.04^{**}$ $0.04^{**}$ $0.04^{**}$ Year: 2011 $0.0003$ $-0.08^{**}$ $-0.08^{**}$ $-0.08^{**}$ $-0.08^{**}$ $-0.08^{**}$ $-0.08^{**}$ $-0.02^{**}$ Year: 2012 $006^{**}$ $011^{**}$ $012^{**}$ $012^{**}$ $012^{**}$ $012^{**}$ $012^{**}$ Year: 2013 $019^{**}$ $019^{**}$ $019^{**}$ $019^{**}$ $019^{**}$ $019^{**}$ $019^{**}$ Age $0.03^{**}$ $0.03^{**}$ $0.03^{**}$ $0.03^{**}$ $0.03^{**}$ $0.03^{**}$ $0.002^{**}$ Age $0.000^{**}$ $0002^{**}$ $0002^{**}$ $0002^{**}$ $0002^{**}$ $0002^{**}$ $0002^{**}$ Age $0.03^{**}$ $0.03^{**}$ $0.03^{**}$ $0.03^{**}$ $0.03^{**}$ $0.0002^{**}$ Age $0.0000^{**}$ $0002^{**}$ $0002^{**}$ $0002^{**}$ $0002^{**}$ Age $0.0000^{**}$ $0002^{**}$ $0002^{*}$ $0002^{*}$ $0002^{*$		-				
Adjacent to Brooklyn R Train       .013**       .015**       .015**       .014**       .014**         Adjacent to Brooklyn R Train       .028*       .0006       .004*       .0021       (0.002)         Year: 2011       .0003       (0.002)       (0.002)       (0.002)       (0.002)       (0.002)         Year: 2012       .006**       .011**      012**       .0103*       .0003**       .003**       .003**       .0003**       .00002**       .0002**       .0002**       .0002**       .00002**       .0002**       .0		(1)	(2)	(3)	(4)	(5)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Adjacent to Brooklyn R Train in 2013	.013**	.015**	.015**	.014**	.014**
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Adjacent to Brooklyn R Train	028**	-0.0006	004**	.004*	.005**
Year: 2011 $0.0003$ $008^{**}$ $008^{**}$ $008^{**}$ $008^{**}$ Year: 2012 $006^{**}$ $011^{**}$ $012^{**}$ $012^{**}$ $012^{**}$ Year: 2013 $019^{**}$ $019^{**}$ $019^{**}$ $019^{**}$ $019^{**}$ $019^{**}$ $019^{**}$ Age $.003^{**}$ $.0002^{**}$ $.0002^{**}$ $.0002^{**}$ $.0002^{**}$ $.0002^{**}$ $.0002^{**}$ $.0002^{**}$ $.0002^{**}$ $.00002^{**}$ $.00002^{**}$ $.00002^{**}$ $.00002^{**}$ $.00002^{**}$ $.00002^{**}$ $.00002^{**}$ $.00002^{**}$ $.00002^{**}$ $.00002^{**}$		(0.0005)	(0.001)	(0.001)	(0.002)	(0.002)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Year: 2011	0.0003	008**	008**	008**	008**
Year: 2012 $006^{**}$ $011^{**}$ $012^{**}$ $012^{**}$ Year: 2013 $019^{**}$ $019^{**}$ $019^{**}$ $019^{**}$ Age $0.003^{**}$ $0.03^{**}$ $0.03^{**}$ $0.03^{**}$ $0.03^{**}$ Age (Squared) $0002^{**}$ $0002^{**}$ $0002^{**}$ $0002^{**}$ $00002^{**}$ $00002^{**}$ Log of Annual Income $085^{**}$ $086^{**}$ $087^{**}$ $087^{**}$ (0.002)       (0.002)       (0.002)       (0.002)       (0.002)         Access to a Vehicle $0.0009$ $-0.002$ $-0.002$ $-0.002$ Migh School Graduate or GED $0.008$ $0.002$ $0.002$ $0.002$ Some College Completed $0.14^{**}$ $0.13^{**}$ $0.13^{**}$ $0.13^{**}$ (0.02)       (0.02)       (0.003)       (0.003)       (0.003)       (0.003)         College Graduate $0.07^{*}$ $0.006$ $0.006$ (0.002)       (0.003)         Master's or Professional Degree $0.07^{*}$ $0.003$ $0.003^{*}$ $0.002^{*}$ $0.002^{*}$ $0.002^{*}$ $0.0$		(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
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Age (Squared) $00002^{**}$ $0002^{**}$			(0.0005)	(0.0005)	(0.0005)	(0.0005)
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Log of Annual Income $085^{**}$ $086^{**}$ $087^{**}$ $087^{**}$ Access to a Vehicle $(0.002)$ $(0.002)$ $(0.002)$ $(0.002)$ Access to a Vehicle $0.0009$ $-0.002$ $-0.002$ $-0.003$ High School Graduate or GED $0.008$ $0.002$ $0.002$ Some College Completed $0.14^{**}$ $0.13^{**}$ $0.13^{**}$ College Graduate $0.14^{**}$ $0.13^{**}$ $0.13^{**}$ College Graduate $0.003$ $(0.003)$ $(0.003)$ Master's or Professional Degree $.007^{*}$ $0.006$ $0.006$ PhD $-0.003$ $-0.002$ $-0.002$ White $.008^{**}$ $.008^{**}$ $.008^{**}$ Black $.019^{**}$ $.019^{**}$ $.019^{**}$ Hispanic $012^{**}$ $012^{**}$ $.012^{**}$ Const. $.116^{**}$ $.886^{**}$ $.879^{**}$ $.879^{**}$ Const. $.116^{**}$ $.886^{**}$ $.879^{**}$ $.879^{**}$ Const. $.0022$ $(0.030)$ $(0.030)$ $(0.030)$			(4.82e-6)	(4.99e-6)	(4.61e-6)	(4.61e-6)
Access to a Vehicle $(0.002)$ $(0.002)$ $(0.002)$ $(0.002)$ $(0.002)$ $(0.002)$ $(0.002)$ $(0.002)$ $(0.002)$ $(0.002)$ $(0.002)$ $(0.003)$ $(0.003)$ High School Graduate or GED $0.008$ $0.002$ $(0.005)$ $(0.005)$ $(0.005)$ $(0.005)$ Some College Completed $0.14**$ $0.13**$ $0.13**$ $0.13**$ $0.13**$ $0.13**$ College Graduate $0.14**$ $0.13**$ $0.15**$ $0.15**$ $0.15**$ Master's or Professional Degree $0.07*$ $0.006$ $0.006$ PhD $0.003$ $(0.003)$ $(0.003)$ $(0.004)$ White $0.03*$ $0.002*$ $0.002*$ $0.002*$ White $0.004*$ $0.004*$ $0.005*$ $0.008**$ Black $0.19**$ $0.19**$ $0.19**$ $0.19**$ Hispanic $-0.12**$ $-0.12**$ $-0.12**$ $-0.12**$ Guo3)Guo4) $0.003$ $0.003$ $0.003$ $0.003$ Storm Damage per Person (\$100s) $0.002$ $0.032$ $0.030$ $0.030$ $0.030$ Const. $.116**$ $.886**$ $.879**$ $.879**$ $.879**$	Log of Annual Income		085**	086**	087**	087**
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High School Graduate or GED $(0.004)$ $(0.003)$ $(0.003)$ Some College Completed $0.008$ $0.002$ $0.002$ $(0.005)$ $(0.005)$ $(0.005)$ $(0.005)$ Some College Completed $0.14**$ $0.13**$ $0.13**$ $(0.003)$ $(0.003)$ $(0.003)$ $(0.003)$ College Graduate $0.13**$ $0.15**$ $0.15**$ $(0.002)$ $(0.003)$ $(0.003)$ $(0.003)$ Master's or Professional Degree $0.07*$ $0.006$ $0.006$ $PhD$ $-0.003$ $-0.002$ $-0.002$ $(0.004)$ $(0.004)$ $(0.004)$ $(0.004)$ $PhD$ $-0.003$ $-0.002$ $-0.002$ $(0.004)$ $(0.004)$ $(0.004)$ $(0.004)$ $PhD$ $-0.023**$ $-0.12**$ $-0.12**$ $(0.003)$ $(0.004)$ $(0.004)$ $(0.004)$ $PhD$ $-0.12**$ $-0.12**$ $-0.12**$ $(0.004)$ $(0.004)$ $(0.004)$ $(0.003)$ $Hispanic$ $-0.23**$ $-0.22**$ $-0.22**$ $(0.003)$ $(0.003)$ $-0.02**$ $-0.02**$ $-0.02**$ $(0.004)$ $(0.003)$ $-0.023**$ $-0.02**$ $-0.02**$ $(0.003)$ $(0.003)$ $-0.009**$ $(0.003)$ $(0.003)$ $(0.004)$ $(0.003)$ $-0.009**$ $(0.003)$ $(0.004)$ $(0.003)$ $-0.009**$ $(0.003)$ $(0.005)$ $-0.002*$ $(0.030)$ $(0.030)$ $(0.002)$ $(0.032)$ $(0.030)$ $(0.030)$	Access to a Vehicle		0.0009	-0.002	-0.002	-0.003
High School Graduate or GED $0.008$ $0.002$ $0.002$ Some College Completed $0.14**$ $0.13**$ $0.13**$ College Graduate $0.13**$ $0.13**$ $0.13**$ College Graduate $0.13**$ $0.15**$ $0.15**$ Master's or Professional Degree $0.07*$ $0.006$ $0.006$ PhD $-0.003$ $-0.002$ $-0.002$ White $-0.003$ $-0.002$ $-0.002$ White $0.004*$ $0.004*$ $0.008**$ Black $0.19**$ $0.19**$ $0.19**$ Hispanic $-0.12**$ $-0.12**$ $-0.12**$ Go.003 $0.004*$ $0.003*$ $0.003*$ Storm Damage per Person (\$100s) $0.002*$ $0.030*$ $0.003*$ Const. $.116**$ $.886**$ $.879**$ $.879**$ $0.002*$ $(0.030)$ $(0.030)$ $(0.30)$			(0.004)	(0.004)	(0.003)	(0.003)
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College Graduate       .013**       .013**       .015**         Master's or Professional Degree       .007*       0.006       0.006         MbD       .003       .0002       .0004       (0.004)         PhD       -0.003       -0.002       -0.002         White       .008**       .008**       .008**         Black       .019**       .019**       .019**         Hispanic      012**      012**       .019**         Storm Damage per Person (\$100s)       .0032)       .0030)       (0.003)         Const.       .116**       .886**       .879**       .879**         .0002)       (0.030)       (0.030)       (0.030)				(0.003)	(0.003)	(0.003)
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Master's or Professional Degree       .00/*       0.006       0.006         PhD       .003       .0.002       .0.002         White       .008**       .008**       .008**         Black       .019**       .019**       .019**         Hispanic       .019**       .019**       .019**         Asian      023**      022**       .002**         Storm Damage per Person (\$100s)       .0009**       .0009**       .0009**         Const.       .116**       .886**       .879**       .879**       .878**	Marta 2 De Caria I Dana			(0.002)	(0.003)	(0.003)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Master's or Professional Degree			.00/*	0.006	0.006
$\begin{array}{cccccccccccccccccccccccccccccccccccc$				(0.003)	(0.004)	(0.004)
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Willie       .008**       .008**       .008**         Black       .019**       .019**       .019**         Hispanic      012**      012**      012**         Asian      023**      023**      022**         Storm Damage per Person (\$100s)       .0009**       .0009**         Const.       .116**       .886**       .879**       .879**       .878**	White			(0.004)	(0.005)	(0.005)
Black       .019**       .019**         Hispanic       .019**       .019**         Asian      012**      012**         Storm Damage per Person (\$100s)       .0009**       .0009**         Const.       .116**       .886**       .879**       .879**       .878**         (0.002)       (0.032)       (0.030)       (0.030)       (0.030)	white				$.008^{**}$	$.008^{**}$
Black       .019**       .019**         Hispanic       (0.004)       (0.004)         Asian      012**      012**         Storm Damage per Person (\$100s)       .0009**       (0.003)         Const.       .116**       .886**       .879**       .879**       .878**         (0.002)       (0.032)       (0.030)       (0.030)       (0.030)	Dlash				(0.0002)	(0.0003)
Hispanic $(0.004)$ $(0.004)$ Asian $012^{**}$ $012^{**}$ Storm Damage per Person (\$100s) $.0009^{**}$ Const. $.116^{**}$ $.886^{**}$ $.879^{**}$ $(0.002)$ $(0.032)$ $(0.030)$ $(0.030)$	DIACK				.019**	(0.004)
Asian $012^{++}$ $012^{++}$ Storm Damage per Person (\$100s) $023^{**}$ $022^{**}$ Const. $.116^{**}$ $.886^{**}$ $.879^{**}$ $.879^{**}$ $(0.003)$ $(0.003)$ $(0.003)$ Const. $.116^{**}$ $.886^{**}$ $.879^{**}$ $.879^{**}$ $(0.002)$ $(0.032)$ $(0.030)$ $(0.030)$	Uispania				(0.004) 012**	(0.004) 012**
Asian      023**      022**         Storm Damage per Person (\$100s)       .0009**         Const.       .116**       .886**       .879**       .879**       .878**         (0.002)       (0.032)       (0.030)       (0.030)       (0.030)	Hispanic				012	012
Asian      022 **         Storm Damage per Person (\$100s)       (0.004)         Const.       .116**         .0002)       (0.032)         .879**       .879**         .878**         (0.002)       (0.032)         .0030)       (0.030)	Asian				(0.003)	(0.003)
Storm Damage per Person (\$100s)       .0009**         Const.       .116**       .886**       .879**       .879**       .878**         (0.002)       (0.032)       (0.030)       (0.030)       (0.030)	Asiali				023	(0.003)
Storm Damage per rerson (\$100\$)       (0.0003)         Const.       .116**       .886**       .879**       .879**       .878**         (0.002)       (0.032)       (0.030)       (0.030)       (0.030)	Storm Damage per Person (\$100s)				(0.004)	(0.003)
Const. $.116^{**}$ $.886^{**}$ $.879^{**}$ $.879^{**}$ $.878^{**}$ (0.002)(0.032)(0.030)(0.030)(0.030)	Storm Damage per l'erson (\$1005)					(0,0003)
(0.002)  (0.032)  (0.030)  (0.030)  (0.030)	Const	116**	886**	870**	870**	878**
(0.052) $(0.052)$ $(0.050)$ $(0.050)$ $(0.050)$	Const.	(0.002)	(0.032)	(0, 030)	(0, 030)	(0, 030)
()bs 136726 136726 136726 136726 136726	Obs	136726	136726	136726	136726	136726
$R^2$ 0,0009 0,375 0,376 0,378 0,378	$R^2$	0 0009	0 375	0 376	0 378	0 378

Table 2: Probability of Being Unemployed, Full Workforce

Significance Levels: \*:5% \*\*:1% | Robust standard errors shown in parentheses

		Monthly	Log		College	Master's		
	Home Value	Rent	Income	Age	Deg.	Deg.	Black	Hispanic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adjacent to Brooklyn R Train in 2013	-300.16	-12.649	0.024	.559**	0.001	009**	.014**	.013**
	(2574.968)	(10.812)	(0.026)	(0.069)	(0.007)	(0.003)	(0.002)	(0.002)
							-	
Adjacent to Brooklyn R Train	183092.40**	219.502**	.327**	477**	.155**	.095**	.339**	.041**
	(725.377)	(2.818)	(0.007)	(0.019)	(0.002)	(0.0008)	(0.0006)	(0.0004)
Year: 2011	-3768.625	-9.609	096**	-0.196	0.005	0.005	0.011	-0.006
	(4649.019)	(30.192)	(0.029)	(0.132)	(0.008)	(0.008)	(0.011)	(0.007)
Year: 2012	-14589.15	45.512	063**	0.024	0.012	0.005	0.004	005*
	(7647.874)	(25.11)	(0.015)	(0.139)	(0.009)	(0.006)	(0.009)	(0.002)
Year: 2013	-7767.52	103.668**	0.006	-0.166	.029**	.013*	-0.007	008**
	(4514)	(19.969)	(0.032)	(0.129)	(0.01)	(0.006)	(0.008)	(0.003)
Const.	520045.60**	1225.348**	9.982**	41.538**	.384**	.152**	.268**	.233**
	(3731.423)	(17.901)	(0.017)	(0.095)	(0.006)	(0.004)	(0.007)	(0.003)
Obs.	54948	76158	136726	136726	136726	136726	136726	136726
R <sup>2</sup>	0.018	0.012	0.001	0.00009	0.006	0.003	0.031	0.0006

**Table 3: Shifts in Demographic Characteristics** 

Significance Levels: \*:5% \*\*:1% | Robust standard errors shown in parentheses

	Vehicle Access	No Vehicle Access	White	Black	Hispanic	Asian
	(1)	(2)	(3)	(4)	(5)	(6)
Adjacent to Brooklyn R Train in						
2013	.007**	.022**	.007	.017**	.034**	.013**
	(.003)	(.002)	(.004)	(.003)	(.004)	(.004)
Adjacent to Brooklyn R Train	.011**	002	.012**	.005**	024**	.004**
	(.001)	(.003)	(.002)	(.002)	(.001)	(.0008)
Year: 2011	008**	008**	006*	.0002	009	018**
	(.002)	(.003)	(.002)	(.004)	(.005)	(.005)
Year: 2012	012**	011**	014**	005	014**	010**
	(.002)	(.002)	(.002)	(.006)	(.004)	(.003)
Year: 2013	017**	022**	016**	021**	020**	019**
	(.004)	(.004)	(.005)	(.005)	(.006)	(.004)
Age	.003**	.003**	.004**	.003**	.002**	.004**
	(.0006)	(.0007)	(.0006)	(.0008)	(.0007)	(.001)
Age (Squared)	00003** (6.44e-06)	00002** (5.67e-06)	00003** (5.65e-06)	00003** (8.45e-06)	00002* (7.56e-06)	00003* (1.00e-05)
Log of Annual Income	086**	088**	081**	091**	090**	084**
-	(.001)	(.003)	(.003)	(.0002)	(.0005)	(.002)
Access to a Vehicle			003	008*	.003	.007*
			(.002)	(.004)	(.007)	(.003)
High School Graduate or GED	.0008	.003	.010	016**	.005	.012**
e	(.007)	(.002)	(.012)	(.002)	(.004)	(.004)
Some College Completed	.010*	.019**	.015**	.007**	.014*	.020**
	(.005)	(.005)	(.004)	(.002)	(.006)	(.004)
College Graduate	.018**	.011	.013**	.004	.006	.031**
	(.004)	(.007)	(.003)	(.005)	(.006)	(.003)
Master's or Professional Degree	006	005	- 001	014**	013**	009**
	(.003)	(.005)	(.005)	(.002)	(.002)	(.002)
PhD	- 002	- 002	- 006	003	- 004	- 006
	(.004)	(.010)	(.006)	(.012)	(.007)	(.006)
White	009**	007**	()	()	()	()
v nice	(002)	(002)				
Black	019**	020*				
Diack	(004)	(000)				
Hispanic	008**	018*				
mspanie	(002)	(009)				
Asian	(.002)	(.00))				
Asian	(003)	027				
Storm Domogo por Dorgon (\$100g)	(.003)	(.007)	001**	0002	004**	001**
Storm Damage per Person (\$1008)	(00003)	(004)	$(001^{11})$	0002	$(004^{++})$	(0004)
Count	(.0001)	(.002)	(.0002)	(.0008)	(.0004)	(.0004)
Collst.	.03/**	.901**	(020)	.908***	.737**	. / 9 / ***
	(.023)	(.039)	(.039)	(.013)	(.023)	(.055)
Oha	70070	57000	67007	24172	21404	21207
$\mathbf{P}^2$	/0020 201	272	212	24173 ADD	J1494 400	∠1∠0/ /1
IV.	.381	.5/5	.515	.477	.402	.41

Table 4: Probability of Being	Unemploy	ved, Sub	populations
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Significance Levels: \*: 5% \*\*: 1% | Robust standard errors shown in parentheses